# Research Background and Perspectives

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## Definition and Applications of SA

#### Sentiment Analysis

Computational examination of sentiments, opinions, and attitudes expressed in text from an opinion holder towards an entity.

#### Sentiment Classification

Determining the polarity of an opinion in a text unit about an entity. It can be document-level, sentence-level or aspect-level.

## Applications

Market surveys and predicitons, brand/product popularity analysis, client/product profiling, political surveys, counter-terrorism, etc.



### Sentiment Classification Tasks

## Sentiment Classification (SC)

The task of determining the polarity of an opinion about an entity.

#### Document-level SC

Performing SC task on a document of a single opinion holder about a single entity.

#### Sentence-level SC

Performing SC task on subjective sentences of one opinion each, from a single opinion holder.

## Aspect-level SC

Performing SC task on different and specific aspects of an entity.



## SA Techniques

SA techniques can be categorized as:

#### • Supervised Learning

- Considering SA as Document Classification
- Pang and Lee, 2002-2005

#### • Semantic orientation and Lexicons

- o PMI-IR algorithm of Turney, 2001
- o WordNet-Affect lexicon

#### Hybrid

- Using lexicons to create training texts
- Seed words extended with synonyms

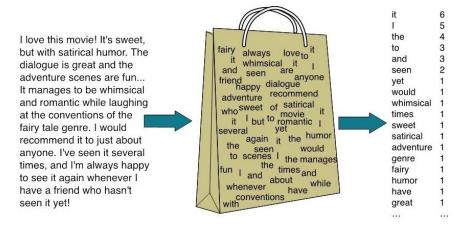


## Text Preprocessing Steps

- Cleaning and Tokenization.
  - Removed remaining html tags.
  - Kept in smiley symbols like :-), :), :(, :-(, :P, :D
- Part of Stopwords removed.
  - Cleared useless terms like "the", "that", "by".
  - Retained negation residues like "don", "didn", "hasn".
- Clipping and Padding.
  - Clipped few very long documents.
  - Zero-padded shorter documents.



## Word Representations: Bag of Words



# Word Representations: Word Embeddings

"You shall know a word by the company it keeps."

– J. R. Firth, 1957

## Word Embeddings

- © Dense and low-dimensional
- $\odot$  Complexity scales linearly w.t.r V
- © Preserve word order in phrases
- © Capture semantic and syntactic similarities
- © Require big text corpora to train
- © Computationally expensive to train



# Representation of Words

Matrix representation of "your shirt looks nice":

	d = 5							
your	0.23	0.18	0.34	0.76	0.62			
shirt	0.64	0.23	0.21	0.03	0.83			
looks	0.98	0.59	0.76	0.65	0.45			
nice	0.11	0.43	0.30	0.22	0.92			

Embeddings sourced from pretrained GoogleNews collection.



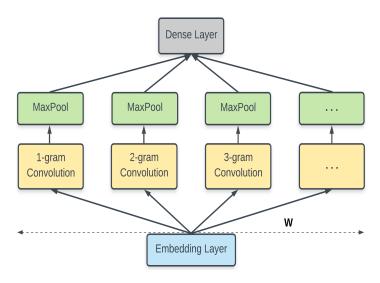
# **Experimental Datasets**

Dataset	Docs	$\mathbf{MinL}$	$\mathbf{AvgL}$	MaxL	$\mathbf{U}\mathbf{sedL}$
Mlpn (song lyrics)	5K	23	227	2733	450
Sent (Sentences)	10K	1	17	46	30
Imdb (movie reviews)	50K	5	204	2174	400
Phon (phone reviews)	232K	3	47	4607	100
Yelp (yelp reviews)	598K	1	122	963	270

- Different domain tasks and data types
- Both small (Mlpn) and big (Yelp) datasets
- Both long (Imdb) and short (Phon) documents

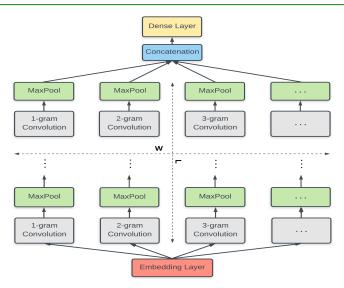


#### Multi-Channel Network Structures



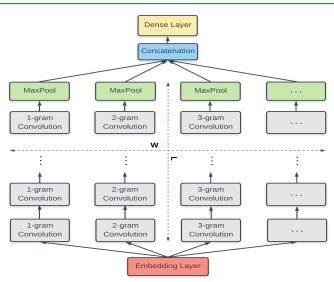


# NgramCNN Basic Architecture



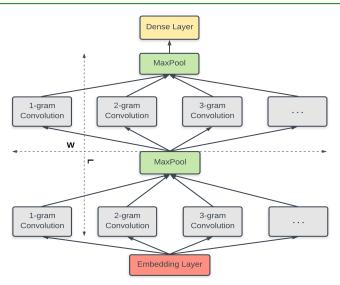


## NgramCNN Pyramid Architecture





## NgramCNN Fluctuating Architecture



## Baseline Models



- Single LSTM
- Single Convolution-Pooling
- Bidirectional LSTM with max-pooling
- Bidirectional LSTM with Convolution-Pooling
- Logistic Regression with tf-idf
- Support Vector Machine with tf-idf



# Comparative Accuracy Scores

Network	Sent	Imdb	Phon	Yelp
NgCNN Basic	79.87	90.77	$\underline{95.92}$	94.88
NgCNN Pyramid	79.52	$\underline{91.21}$	95.70	94.83
NgCNN Fluctuate	77.41	89.32	93.45	92.27
Optimized LR	81.63	89.48	92.46	91.75
Optimized SVM	82.06	88.53	92.67	92.36
SingleCNN	81.79	89.84	94.25	93.86
SingleLSTM	80.33	84.93	93.71	90.22
BLSTM-POOL	80.96	85.54	94.33	91.19
BLSTM-2DCNN	82.32	85.70	95.52	91.48

# Further Observations



- Deep feature networks with simple classifiers are top performers on texts, same as on images.
- Basic NgramCNN architecture is fast and highly accurate on long documents.
- LSTM-based architectures are slower to train and perform poorly on long documents.
- For small datasets, traditional linear classifiers like LR or SVM could be good enough.

[4] E. Çano, M. Morisio: A Deep Learning Architecture for Sentiment Analysis

## More about me...



Old Website: http://softeng.polito.it/erion

New Website: https://ufal.mff.cuni.cz/erion-cano









### **Definition of Text Summarization**

## Text Summarization (TS)

Distilling the most important information in a text to produce an abridged version.

## Types of TS

- Single-document vs Multi-document
- Extractive vs Abstractive
- Generic vs Query-driven
- Informative vs Indicative







- Simplify and abbreviate text (Abstracts)
- Summary of email threads (Subjects)
- Action items from a meeting (Discussions)
- Generating news of an event (Stories)
- Basic opinions about an item (Reviews)
- Answering user questions (Queries)



### Extractive vs Abstractive

#### Extractive TS

The generated summary is a selection of relevant sentences from the source text in a copy-paste fashion.

- Simpler and highly explored
- Statistical, Feature-based, Machine Learning, Graph-based

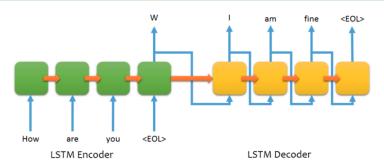
#### Abstractive TS

The generated summary is a new cohesive text not necessarily present in the original source.

- Hard and challanging
- TS as a neural MT problem; encoder-decoder paradigm



## Abstractive TS Problems



#### **Problems**

- Generated summary not always meaningful
- Ambiguity to distinguish rare and unknown words
- Grammar errors in the generated summaries



## Ideas to Explore

- Infuse prior knowledge like POS tagging
- Infuse other hand-crafted linguistic features
- Inject relational semantic knowledge
- Explore other networks structures or architectures
- ...?



# Questions or Suggestions...?



Thank You... ②